mathematics

Article

New Product Idea Selection in the Fuzzy Front End of Innovation: A Fuzzy Best-Worst Method and Group Decision-Making Process

Shui Ming Li [1], Felix T. S. Chan [1], Yung Po Tsang [1,*] and Hoi Yan Lam [2]

[1] Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Kowloon, Hong Kong, China; richard-sm.li@connect.polyu.hk (S.M.L.); f.chan@polyu.edu.hk (F.T.S.C.)
[2] Department of Supply Chain and Information Management, The Hang Seng University of Hong Kong, Shatin, Hong Kong, China; cathylam@hsu.edu.hk
* Correspondence: p.tsang@connect.polyu.hk

Abstract: New product development (NPD) is essential to most business organizations to create new values and protect existing values for maintaining high profitability and sustainability. However, the success of NPD projects is deemed to be difficult and challenging owing to high organizational complexity, uncertain business environment, and time-critical innovation. Under the smart manufacturing paradigm, NPD is an active research area to establish effective measures through the adoption of systematic approaches so as to facilitate idea management in the fuzzy front end for the product innovation. In this paper, the domain of new product idea selection is focused on and enhanced by means of the multi-criteria decision-making (MCDM) approach, in which multiple criteria and sub-criteria can be considered in the selection process. Among a number of MCDM approaches, the fuzzy set theory and best-worst method (BWM) are integrated as the fuzzy BWM in this study to structure the new product idea selection process under a group decision-making process. The hierarchy structure for the new product idea selection is also established to consider the perspectives of finance, marketing, engineering, manufacturing, and sustainability. Overall speaking, this study contributes to the field of NPD through overcoming the new product idea selection problem, while the group decision-making process is incorporated into the fuzzy BWM.

Keywords: new product development; idea selection; fuzzy set; multi-criteria decision-making; best worst method; group decision-making

Citation: Li, S.M.; Chan, F.T.S.; Tsang, Y.P.; Lam, H.Y. New Product Idea Selection in the Fuzzy Front End of Innovation: A Fuzzy Best-Worst Method and Group Decision-Making Process. *Mathematics* **2021**, *9*, 337. https://doi.org/10.3390/math9040337

Academic Editor: Gustavo Santos-García
Received: 18 January 2021
Accepted: 3 February 2021
Published: 8 February 2021

1. Introduction

The core objective of this study is to include group decision-making in the fuzzy best-worst method to address the new product idea selection problem considering the criteria of finance, marketing, engineering, manufacturing, and sustainability. Under the demanding and fiercely competitive business environment, new product development (NPD) is of utmost importance to introduce products and services to the market with satisfying market opportunities and customer needs. Generally speaking, new products should be launched in a cost-effective manner, with a designated quality level, and at the right period of time so as to truly meet customer requirements and increase the market share of companies. Although the NPD is essential to every company, particularly in the manufacturing industry, which affects the production planning and strategies throughout the entire product lifecycle, there are plenty of existing uncertainties and challenges to hinder the development of the NPD process. For instance, shortening product life cycles, fluctuations of supply chains, and uncertainty in the demand forecasting are proven as the critical challenges in the NPD-related research studies [1,2]. According to the report related to product management [3], 95% of all new consumer products have failed in each year, representing more than 30,000 new products, in which only 24% of developed products can generate revenue during business activities. In addition, merely 11% of new products keep consumers engaged after a year, which shows that the market for new products is highly frustrating and uncertain, and thus comprehensive preparation before launching new products to the market is regarded as the most crucial element to companies. Normally, reaching the highest distribution of a new product requires 28 weeks, in which the creativity and product innovation are the major incentives for purchasing by end customers. Therefore, when developing new products, the motivations, target customers, competitiveness, and manufacturing capability should be considered to drive the success of the NPD process. In view of the NPD process, there are eight generic steps to include all possible activities, namely, new product strategy, idea generation, screening, concept testing, business analysis, product development, marketing testing, and commercialization [4,5]. The above structured process can lead to the accomplishment of NPD step by step. Clear goals and objectives for the NPD process can be defined in advance, so as to generate appropriate ideas meeting requirements from companies and customers. After selecting the most suitable idea, the realization of the idea into a proof of concept, or even formal product development, can be achieved, in which in-depth evaluations on costs and quality can be conducted to ensure the practicality of new product concepts. Subsequently, the new products can be developed for conducting the trail runs in the market to examine the market reaction and opportunities. To generate a customer-centric, sustainable, and innovative new product design, a great deal of market and customer information should be considered at the early stage of the whole NPD process.

As shown in Figure 1, the fuzzy front end (FFE) is a specific terminology in the NPD to represent the messy growing period, in which a great deal of decisions, such as "to invest or not to invest", are considered by companies. Moreover, data analytics and prediction on sales performance of new products are especially important to understand the market situation. In order to overcome the challenges in the current business environment, an intelligent approach to select the appropriate new product ideas is needed to improve the effectiveness and efficiency of product development, and to sustain the entire NPD process. In this paper, the hierarchical structure for the new product idea selection is established, while a multi-criteria decision-making (MCDM) method is adopted as a systematic approach to select the most appropriate idea for entering the formal product development process. In summary, the contribution of this study can be presented in two facets. Firstly, the new product idea selection problem in the domain of NPD is addressed by considering five essential perspectives, covering finance, marketing, engineering, manufacturing, and sustainability, with 15 sub-criteria, resulting in achieving sustainable NPD in the industry. Secondly, fuzzy set theory is incorporated into the best-worst method (BWM) to address the subjective judgements in pairwise comparisons, while group decision-making is considered to enrich the practicality and reliability of the new product idea selection process.

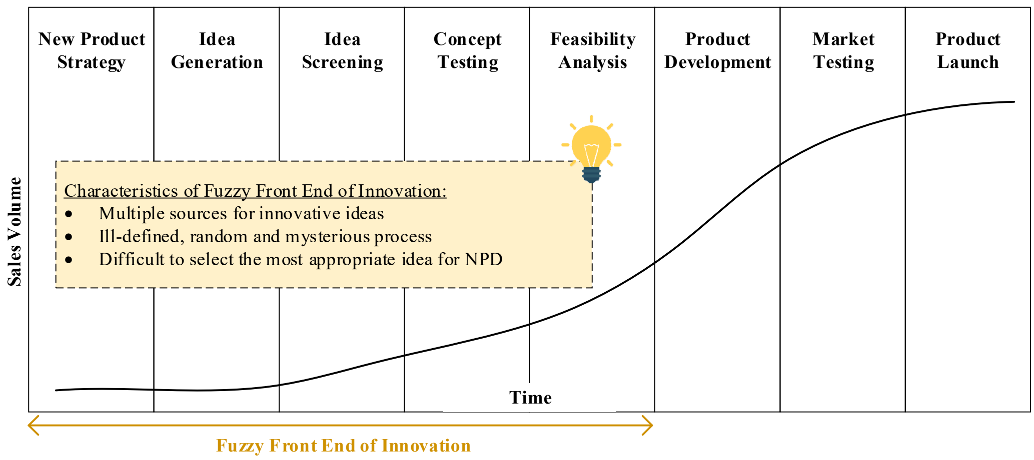

Figure 1. Fuzzy front end of innovation in the entire new product development (NPD) process.

The remainder of this paper is organized as follows. Section 2 reviews the past literature concerning new product development, idea selection, and multi-criteria decision-making approaches. Section 3 presents the architecture and details of the proposed methodology. Section 4 presents a case study to examine the feasibility of the proposed methodology in the electronics industry. Section 5 discusses the results and discussion on its values and implications. Finally, Section 6 provides the conclusions.

2. Literature Review

In this section, the recent literature in the area of new product development, idea selection, and multi-criteria decision-making approaches is reviewed to identify the research gap, allowing corresponding measures to address this gap to be determined.

2.1. Overview of New Product Development

Product design and development are important as life cycles of new products are becoming shorter in recent years. It is presented that the importance of new product development (NPD) has been greatly increased, which is one of the essential factors for companies' survival in various industries, such as electronic products [6]. Before conducting mass production in the manufacturing sites, NPD management is employed to control the costs and time involved in the manufacturing process from some initial ideas to the production discontinuation. Effective NPD management can improve the competitiveness of the companies in the market, and sustain the electronics manufacturing industry [7]. In addition, five general stages for the NPD model are described, covering (i) scoping, (ii) building business case, (iii) development, (iv) testing and validation, and (v) launching [8]. In the above NPD stages, the factors of result-orientation, customer perspective, and strategy are significant in the performance of NPD process [9]. In order to prevent the failures of NPD, a number of scholars and industrial practitioners have been investigating different kinds of measures on analysing the NPD process in aspects of theory, simulation, and prediction. Some of them adopt the axiomatic design (AD) and theory of inventive problem solving (TRIZ) to support the innovation process, such that the innovative elements can be created in existing products to address outstanding needs from customers and markets [10]. Moreover, customer participation in the NPD process is promising nowadays as a form of co-creation so that companies and customers can work together to establish better new products [11]. Apart from satisfying the customer demands, recent new product designs tend to be more sustainable and greener to the world, while waste in the NPD process should be eliminated [12–14]. Subsequently, sustainability on NPD becomes a critical factor to determine the success of the NPD process. When understanding the eco-system of the NPD, it is implied that a good beginning of the NPD, i.e., selection of the appropriate new product ideas and designs, become significantly important. Given that the smart manufacturing is being studied and developed extensively, the determination of the new product ideas can become data-driven through considering customer data, market data, historical product performance, and so on. Therefore, the evolution of the new product idea selection should be investigated in the era of smart manufacturing.

2.2. New Product Idea Selection

In the NPD process, the first and foremost step is to select the ideas that are the most profitable, manufacturable, and sustainable in the market among all other alternatives, and thus an ontology of new product idea selection (NPIS) has drawn significantly attention from academics and industrial practitioners. Because of the limited information and understanding on customers and markets at the FFE stage, developing an effective scheme for NPIS is challenging and complicated [15,16]. In principle, there are 11 types of approaches for achieving NPIS, namely, technical analysis, marketing analysis, financial analysis, organisational analysis, strategic analysis, relationship analysis, industrial analysis, competitive analysis, similar case analysis, consumer and consumption analysis, and expert analysis [17]. This shows that the factors considered in the NPIS process have different dimensions, such that a balance between various criteria should be struck. Subsequently, there is a need for an integrated solution for achieving effective NPIS, which can consider multiple criteria in the current business environment. Because of the dawn of industry 4.0, the data collection, management, and analysis have been greatly improved and structured, which can also benefit the NPD process. Under the industry 4.0 framework, some digital tools may assist the product development and prototyping processes to align with the lean principles, where additional value can be created to customers in an effective and consistent manner [18]. Regarding the development of effective NPIS, a decision analysis method that can evaluate multiple criteria is preferred in the market, and thus a balance between finance, business strategies, customer perspectives, and engineering requirements can be made.

2.3. Multi-Criteria Decision-Making Approaches

To address the above challenges of the NPIS, multi-criteria decision-making (MCDM) approaches are promising to rank a set of alternatives through conducting pairwise comparison between various criteria in the problem domain. It has been widely explored to solve several industrial problems, such as system assessment [19], priority evaluation [20], and software selection [21]. Among various multi-criteria decision-making (MCDM) methods, the best-worst method (BWM) is the vector-based technique used to make selection decisions based on defined criteria and sub-criteria [22]. It is a five-step approach to derive the weights between various options in the problem domain, in which the consistency ratio can be evaluated to ensure the reliability of the entire method. Moreover, the work [22] reported that the performance of BWM is better than another well-known and well-established MCDM method, i.e., analytical hierarchy process (AHP), in four dimensions, namely, (i) less complexity, (ii) robust reliability measurement, (iii) high compatibility with other methods, and (iv) high simplicity of the data collection. This method can be further applied in several real-life situations, such as new product idea selection in the NPD process. In order to handle the vagueness and uncertainty in the problem domain, the fuzzy BWM was also invented to achieve reliable results for the ambiguity of the decision maker [23]. Additional flexibility can be obtained using the fuzzy BWM in the MCDM process, in which the use of linguistic terms, for example, equally important, weakly important, and very important, can be utilized to rate various criteria. Apart from discussing the differences between AHP and BWM, the techniques for order preference by similarity to an ideal solution (TOPSIS) and KOmpromisno Rangiranje (VIKOR) are two well-known MCDM approaches used to achieve effective alternative prioritization [24]. Compared with AHP and BWM, TOPSIS and VOKOR were designed to assess the cardinal absolute measurements, such as positive and negative ideal solutions, based on non-comparable and conflicting criteria. Although the above methods are promising to prioritize alternatives with conflicting criteria, the measurement consistency cannot be simply tested by evaluating their consistency ratios. The above methods can contribute to the domain of new product idea selection as a robust and efficient method to evaluate the weights between various criteria and sub-criteria, while the aggregated results can be generated.

2.4. Research Directions on Current NPD

After the above literature is reviewed, it is found that the FFE stage, i.e., the first and beginning step, of the entire NPD process should be focused on, in which the NPIS is regarded as the essential domain to determine the most appropriate new product idea for conducting the formal product development process. By doing so, MCDM approaches should be considered to establish a systematic methodology for considering various factors and criteria related to the NPIS. Among numerous MCDM approaches, the fuzzy BWM is exploited to build the methodology of the NPIS in this study, and thus decision makers in the product development team can systematically rank a set of idea alternatives.

3. Methodology for the Multi-Criteria New Product Idea Selection

This section describes a methodology for achieving effective NPIS by means of fuzzy BWM. It consists of two major phases, namely (i) hierarchical structure for state-of-the-art NPIS, and (ii) fuzzy BWM for the NPIS. Overall, a systematic approach is developed for conducting pairwise comparisons by decision makers to rank and select the most appropriate new product idea for companies.

3.1. Hierarchical Structure for State-of-the-Art NPIS

To structure the NPIS, Figure 2 shows the three-level hierarchy for showing the considered criteria and sub-criteria for selecting the best new product idea. The criteria and sub-criteria are consolidated from the past literature [5,25–27]. With the goal of the new product idea selection (at level 0), five criteria are summarised, namely, finance (C1), marketing (C2), engineering (C3), manufacturing (C4), and sustainability (C5), which are the major dimensions for evaluating the new product ideas. Finance (C1) refers to the financial performance along the entire product lifecycle from product development to recycling of damaged products, and it is measured by three sub-criteria, namely, return on investment (C11), cost of product lifecycle (C12), and cost of failure (C13). For marketing (C2), the effectiveness of promoting new products to create values on customers and companies is also concerned, which is evaluated by market penetration (C21), customer value (C22), and brand building (C23). For engineering (C3), an engineering perspective to design and develop new product ideas is considered, which aims to construct novel and high-quality new products for the market. It is thus examined by novelty (C31), time to market (C32), and product quality audits (C33). For manufacturing (C4), apart from engineering aspect, the production of new product ideas into new products should be included at the beginning planning stage, through inspecting the prototypes of new product ideas. It can be initially inspected by expertise requirements (C41), production throughput (C42), and first pass yield (C43). For sustainability (C5), the modern NPD is aligned to green initiatives for establishing the circular economy in the market, which has equal importance to profitability and customer values. It is assessed by ease of recycling (C51), energy consumption (C52), and carbon footprint (C53). To adopt the MCDM in the NPIS, pairwise comparisons in levels 1, 2, and 3 are conducted. For level 1, the adjusted weights between four criteria can be evaluated to support the weight composition for the alternatives. Similarly, the weights between sub-criteria in the same criterion category are determined for the composition of weights for the NPIS. For level 3, the pairwise comparisons for each sub-criterion between five alternatives are conducted to evaluate the priority vectors for the alternatives. Eventually, the weights can be composited together to generate resultant weights for the alternatives.

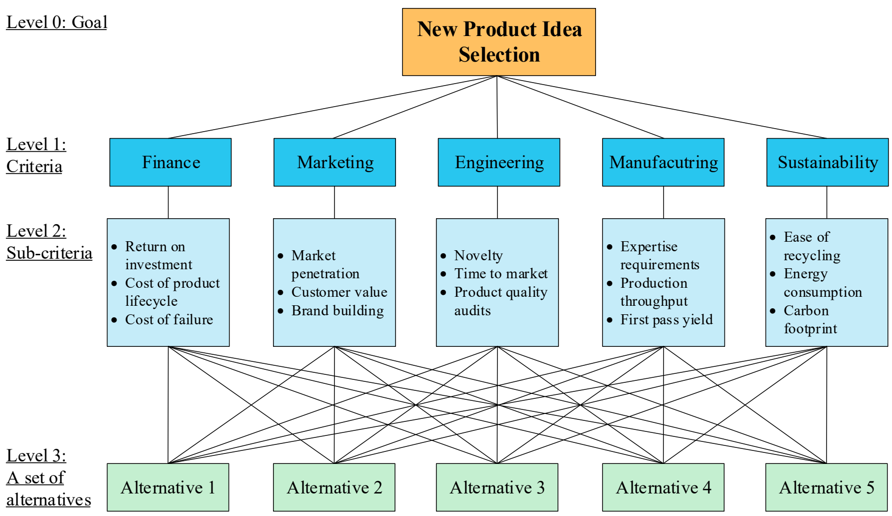

Figure 2. Hierarchical structure for new product idea selection.

3.2. Fuzzy Best-Worst Method for the NPIS

In order to select the most suitable new product idea, the fuzzy BWM, which is promising to determine fuzzy weights of criteria and sub-criteria, is adopted in the proposed model [23]. Instead of assigning the Saaty's scale on the pairwise comparisons, a set of linguistic terms associated with the corresponding triangular fuzzy numbers are applied for enhanced ease of data collection. After conducting the fuzzy BWM, the weights of criteria and sub-criteria are presented in the form of triangular fuzzy numbers, called fuzzy weights, which requires a de-fuzzificiation process to convert into crisp values. Such an approach can contribute to the area of new product idea selection by considering various criteria and sub-criteria defined in the hierarchical structure. Figure 3 shows the mechanism of using the fuzzy BWM to rank a set of alternatives for the NPIS.

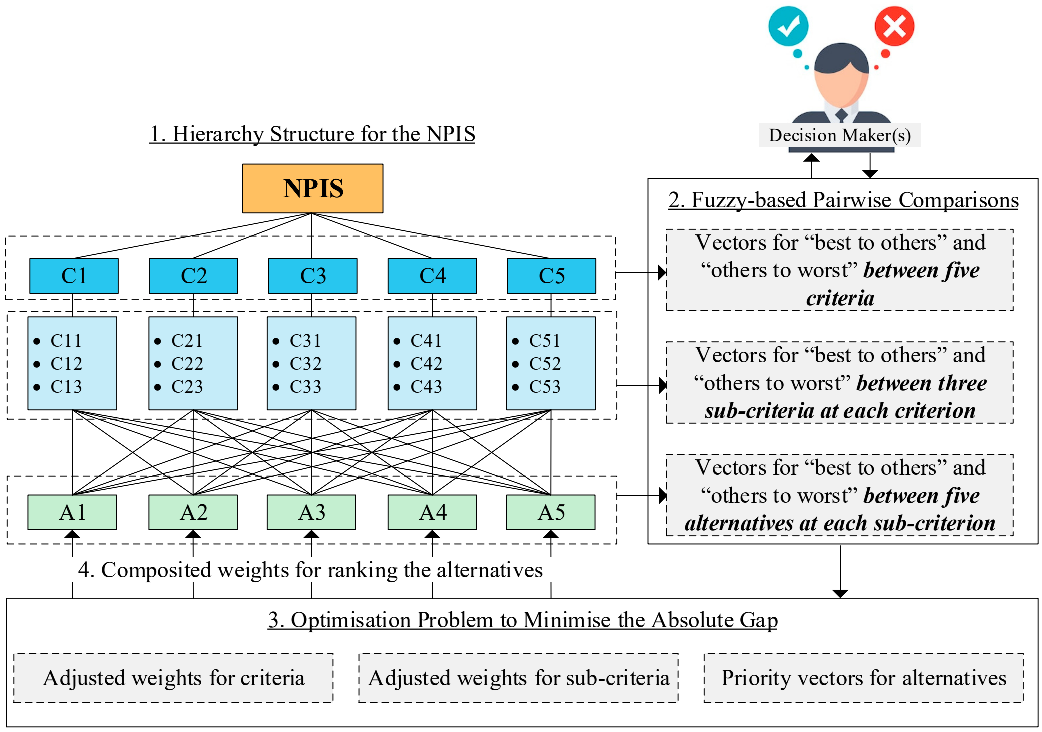

Figure 3. Process flow of using the fuzzy best-worst method (BWM). NPIS, new product idea selection.

According to the hierarchy structure, the goal, criteria, sub-criteria, and alternatives are defined for the new product idea selection problem, with n criteria and $n \times m$ sub-criteria, namely, $C_n = \{C_1, C_2, \ldots, C_n\}$ and $C_{nm} = \{C_{11}, C_{12}, \ldots, C_{1m}, C_{21}, \ldots, C_{2m}, \ldots, C_{nm}\}$, respectively. From the fuzzy BWM, the best (most important) and worst (least important) factors, which are the criteria or sub-criteria, are identified in each pairwise comparison to evaluate the weights, where the best and worst criteria are labelled as C^b and C^w, respectively. Subsequently, the fuzzy reference comparisons can be conducted for the pairwise comparisons with two scenarios, namely (i) between the best criteria and the others and (ii) between the worst criteria and the others. Each pairwise comparison is conducted by using linguistic terms, and the linguistics term i is represented by triangular fuzzy numbers (l_i, m_i, u_i), where l_i, m_i, and u_i denote the lower bound, mid-point, and upper bound for the linguistic term, respectively. For example, the linguistics term "weakly important" can be represented by the triangular fuzzy number (1, 2, 3). According to the defined hierarchical structure, the pairwise comparisons are conducted in three scenarios: (i) between five criteria, (ii) between three sub-criteria at each criterion, and (iii) between five alternatives at each sub-criterion. Moreover, the equivalent fuzzy number of the triangular fuzzy number can be calculated using graded mean integration representation

(GMIR), which is referred to as the graded λ-preference integration representation (where λ = 1/2 and k = 1).

To deal with the computations in the optimisation problem in the fuzzy BWM, two definitions, namely (i) operations of triangular fuzzy numbers and (ii) GMIR of triangular fuzzy numbers, are elaborated as follows:

Definition 1. *Let linguistic terms A and B be associated with triangular fuzzy numbers (l_A, m_A, u_A) and (l_B, m_B, u_B), respectively, where $-\infty < l_A \leq m_A \leq u_A < \infty$ and $-\infty < l_B \leq m_B \leq u_B < \infty$. The addition and subtraction between two triangular fuzzy numbers are referred to in Equations (8) and (9) [28].*

$$(l_A, m_A, u_A) \oplus (l_B, m_B, u_B) = (l_A + l_B, m_A + m_B, u_A + u_B) \tag{1}$$

$$(l_A, m_A, u_A) \ominus (l_B, m_B, u_B) = (l_A - u_B, m_A - m_B, u_A - l_B) \tag{2}$$

Moreover, assuming that two fuzzy numbers are on the same sign, the multiplication and division between two triangular fuzzy numbers are referred to in Equations (10) and (11) [28].

$$(l_A, m_A, u_A) \otimes (l_B, m_B, u_B) = [\min(l_A l_B, l_A u_B, u_A l_B, u_A u_B), m_A m_B, \max(l_A l_B, l_A u_B, u_A l_B, u_A u_B)] \tag{3}$$

$$\frac{(l_A, m_A, u_A)}{(l_B, m_B, u_B)} = \left[\min(\frac{l_A}{l_B}, \frac{l_A}{u_B}, \frac{u_A}{l_B}, \frac{u_A}{u_B}), \frac{m_A}{m_B}, \max(\frac{l_A}{l_B}, \frac{l_A}{u_B}, \frac{u_A}{l_B}, \frac{u_A}{u_B})\right] \tag{4}$$

Definition 2. *The evaluation of GMIR for a triangular fuzzy number is rooted from graded λ-preference integration representation, where λ = 1/2 at 1st order plane curve fuzzy numbers (k = 1) for the linguistic term A associated with triangular fuzzy number (l_A, m_A, u_A) [29], as in Equation (5).*

$$\mathrm{GMIR}(A) = \frac{l_A + 4m_A + u_A}{6} \tag{5}$$

When decision makers assign the appropriate rates in the pairwise comparison, the corresponding vectors can be formulated to optimize fuzzy weights. The objective to determine the optimal fuzzy weights is to minimize the absolute gap ξ such that the differences between w_b/w_j and triangular fuzzy number of the best criterion A_b, and between w_j/w_w and triangular fuzzy number of the worst criterion A_w, are minimized. The factors w_b, w_w, and w_j denote the weights to be determined for the best criterion, the worst criterion, and other criteria j, respectively. The objective function for minimizing the absolute gap ξ, which is the k value in (l, m, u), is formulated, as in Equation (6). The constraints of this optimization problem are presented as follows: constraint (7) examines the absolute gap between the w_b/w_j and triangular fuzzy number of the best criterion A_b, which is limited to ξ; similarly, constraint (8) examines the absolute gap between the w_j/w_w and triangular fuzzy number of the best criterion A_w, which is limited to ξ; constraint (9) calculates the triangular fuzzy number using GMIR, and the sum of GMIR among all criteria is equal to 1; constraint (10) ensures the reasonable range of triangular fuzzy number (l, m, u); and constraint (11) ensures the non-negativity integrality of the absolute gap ξ.

$$\min.\ \xi = (k,\ k,\ k) \tag{6}$$

Subject to the following:

$$\left|\frac{w_b}{w_j} - (l_{Bj},\ m_{Bj},\ u_{Bj})\right| = \left|\frac{(l_B,\ m_B,\ u_B)}{(l_j,\ m_j,\ u_j)} - (l_{Bj},\ m_{Bj},\ u_{Bj})\right| \leq \xi \tag{7}$$

$$\left| \frac{w_j}{w_w} - (l_{jw},\ m_{jw},\ u_{jw}) \right| = \left| \frac{(l_j,\ m_j,\ u_j)}{(l_w,\ m_w,\ u_w)} - (l_{jw},\ m_{jw},\ u_{jw}) \right| \leq \xi \tag{8}$$

$$\sum_{j=1}^{n} R(w_j) = 1 \tag{9}$$

$$0 \leq l_j\ \leq m_j\ \leq u_j \tag{10}$$

$$\xi \geq 0 \tag{11}$$

Therefore, the outcome of this optimization problem determines the value of the absolute gap ξ, and fuzzy weights of the major criteria and sub-criteria for the NPIS. After the optimisation problems to minimise the absolute gaps are solved, the results of (i) adjusted weights of criteria ω_i for the major criterion i, (ii) adjusted weights of sub-criteria ω_{ij} for sub-criterion j under criterion i, and (iii) priority vector v_{ijk} for sub-criterion j under criterion i at alternative k can be obtained. From the priority vector, the value v_{ijk} represents the specific priority value of the alternative under the designated criteria and sub-criteria. Eventually, the composited weight γ_k for alternative i can be computed by aggregating the adjusted weights and priority vectors, as in Equation (12), where there are five criteria and each criterion has three corresponding sub-criteria. The sum of products between values of the priority vector and weights of three sub-criteria are calculated, which are used to compute the sum of products with five major criteria. Therefore, the new product ideas can be ranked in a systematic manner, while the most appropriate idea with respect to five dimensions can be selected. Regarding the group decision-making process, the finalized weight $\overline{\gamma_k}$ for alternative k is updated by averaging all composited weights from the total number of decision makers.

$$\gamma_k = \sum_{i=1}^{5} [\omega_i \cdot (\sum_{j=1}^{3} \omega_{ij} v_{ijk})] \tag{12}$$

4. Case Study in the Electronics Manufacturing Industry

In order to examine the feasibility of the proposed system, a case study is illustrated in this section, along with the detail implementation procedures on adopting the fuzzy BWM on the defined hierarchical structure for the NPIS. Therefore, the case company can select the most appropriate new product ideas effectively and systematically.

4.1. Industrial Problems and Motivations

In this case study, a case company, named Gainscha, located in Zhuhai, China was selected, which has active business in manufacturing and selling various types of printing machines to worldwide industrial customers. For example, home printers, industrial printing solutions, and commercial printers are included in its business scope. The printers manufactured by the case company target improving the efficiency and effectiveness of various industries, such as logistics and supply chain and e-businesses. It provides more than ten types of printers, such as thermal printers, dot matrix printers, and barcode printers, to cater for industrial needs and requirements. The case company is eager to develop the printers with innovative features to improve its reputation and sales performance. Therefore, it has a research and development (R&D) team to design and develop new products for catching the emerging trends in the market. For instance, it introduced a cloud-based printing solution that integrates online payment, cloud computing, and mobile application development to facilitate mobile printing operations, and can be applied in food delivery, logistics, ticket selling, hotels, and hospitals. Consequently, the productivity of the businesses can be improved, while the process flows of the businesses are further smoothened.

As mentioned above, the case company is dedicated to developing new products to satisfy the demanding customer requirements in the market by embedding new technologies. However, new product development is not started until the presence of the customer requirements, which may lag the trends of the market. Moreover, the entire NPD process takes a relatively long period of time, normally two to three years from the ideas to the mass production. Thus, the R&D team in the case company needs to select the most appropriate new product ideas among a large potential idea pool to maximize the profitability, sustainability, and product attractiveness in the market. The NPIS is essential for the case company to select the most suitable idea in a systematic manner. Moreover, it needs to predict the market needs and to research emerging technologies for the enhancement of printing solutions. In order address the above concerns, a decision support system to provide accurate decisions on NPIS is needed for the NPD process in the manufacturing industry. The efficient way to make the decisions on new product idea selection through considering multiple criteria and sub-criteria can be constructed.

4.2. Implementation of the Proposed Methodology

In order to resolve the challenges related to NPIS in the case company, the proposed methodology is adopted to let decision makers, for example, R&D managers, select the most suitable new product idea in the aspects of finance, marketing, engineering, manufacturing, and sustainability. The entire implementation of the proposed methodology is divided into three parts, namely, (i) pairwise comparisons by decision makers, (ii) minimization of the absolute gaps using the fuzzy BWM, and (iii) weight aggregation and idea ranking.

4.2.1. Pairwise Comparisons by Decision Makers

In the first step, the pairwise comparisons by the decision makers, namely the R&D manager and assistant managers in this case study, are conducted. As shown in Figure 3, three sets of pairwise comparisons should be considered, namely, (i) between five criteria, (ii) between three sub-criteria at each criterion category, and (iii) between five alternatives at each sub-criterion. To rate in the pairwise comparisons, the decision makers can simply use some natural expression intuitively, instead of following the rating scales. Subsequently, the pairwise comparisons for levels 1 and 2 are conducted using the linguistic values according to the Saaty's scale, which are divided into five levels as shown in Table 1 [30]. Similarly, the conversion between linguistic terms and triangular fuzzy number for level 3 is shown in Table 2. Therefore, the decision makers in this case study can assign the appropriate rating in the structured pairwise comparisons using the linguistic terms, instead of exact numerical values. Regarding the hierarchical structure presented in Figure 2, one, five, and fifteen pairwise comparisons should be conducted for level 1, 2, and 3, respectively, while twenty-one pairwise comparisons in total for best-to-others (B2O) and others-to-worst (O2W) are established.

Table 1. Conversion of linguistic terms at levels 1, 2, and 3.

Linguistic Terms	Label of Linguistic Terms	Triangular Fuzzy Number	GMIR
Equally important/Equally excellent	EI/EE	(1, 1, 1)	1
Little important/Least excellent	LI/LE	(2, 3, 4)	3
Strongly important/Moderate excellent	SI/ME	(4, 5, 6)	5
Very Important/Very excellent	VI/VE	(6, 7, 8)	7
Absolutely important/Absolutely excellent	AI/AE	(8, 9, 9)	9

Table 2. Pairwise comparison at level 1 from a decision maker.

Level 1 between C1, C2, C3, C4, C5					
Best-to-others	C1	C2	C3	C4	C5
C1 (Best)	-	SI	VI	AI	LI
Others-to-worst	C1	C2	C3	C4	C5
C4 (Worst)	AI	SI	LI	-	SI

As shown in Tables 2–4, the opinion from one of the decision makers for the NPIS has been collected. At levels 1 and 2, the decision maker is required to rate the criteria and sub-criteria according to its importance, thus the most important criteria can be identified. On the other hand, at level 3, the pairwise comparisons can examine the superiority of the alternatives with respect to each sub-criterion. Subsequently, the fuzzy BWM can be applied to evaluate the collected ratings in pairwise comparisons to establish a systematic process for the NPIS.

Table 3. Pairwise comparisons at level 2 from a decision maker.

Level 2 between C11, C12, C13			
Best-to-others	C11	C12	C13
C11(Best)	-	VI	SI
Others-to-worst	C11	C12	C13
C12 (Worst)	VI	-	LI
Level 2 between C21, C22, C23			
Best-to-others	C21	C22	C23
C22 (Best)	SI	-	AI
Others-to-worst	C21	C22	C23
C23 (Worst)	LI	AI	-
Level 2 between C31, C32, C33			
Best-to-others	C31	C32	C33
C33 (Best)	VI	LI	-
Others-to-worst	C31	C32	C33
C31 (Worst)	-	SI	VI
Level 2 between C41, C42, C43			
Best-to-others	C41	C42	C43
C43 (Best)	SI	LI	-
Others-to-worst	C41	C42	C43
C42 (Worst)	LI	-	LI
Level 2 between C51, C52, C53			
Best-to-others	C51	C52	C53
C53 (Best)	AI	LI	-
Others-to-worst	C51	C52	C53
C51 (Worst)	-	SI	AI

Table 4. Pairwise comparison at level 3 from a decision maker.

Level 3 between A1, A2, A3, A4, A5 for C11					
Best-to-others	A1	A2	A3	A4	A5
A2 (Best)	ME	-	VE	LE	ME
Others-to-worst	A1	A2	A3	A4	A5
A5 (Worst)	LE	ME	AE	ME	-
Level 3 between A1, A2, A3, A4, A5 for C12					
Best-to-others	A1	A2	A3	A4	A5
A1 (Best)	-	VE	LE	LE	ME
Others-to-worst	A1	A2	A3	A4	A5
A3 (Worst)	LE	AE	-	LE	ME
Level 3 between A1, A2, A3, A4, A5 for C13					
Best-to-others	A1	A2	A3	A4	A5
A1 (Best)	-	ME	ME	LE	LE
Others-to-worst	A1	A2	A3	A4	A5
A5 (Worst)	LE	VE	ME	ME	-

Table 4. *Cont.*

Level 3 between A1, A2, A3, A4, A5 for C21					
Best-to-others	A1	A2	A3	A4	A5
A4 (Best)	AE	VE	LE	-	ME
Others-to-worst	A1	A2	A3	A4	A5
A5 (Worst)	VE	ME	LE	ME	-
Level 3 between A1, A2, A3, A4, A5 for C22					
Best-to-others	A1	A2	A3	A4	A5
A2 (Best)	LE	-	ME	VE	LE
Others-to-worst	A1	A2	A3	A4	A5
A3 (Worst)	VE	ME	-	ME	LE
Level 3 between A1, A2, A3, A4, A5 for C23					
Best-to-others	A1	A2	A3	A4	A5
A4 (Best)	ME	AE	LE	-	ME
Others-to-worst	A1	A2	A3	A4	A5
A5 (Worst)	LE	VE	ME	ME	-
Level 3 between A1, A2, A3, A4, A5 for C31					
Best-to-others	A1	A2	A3	A4	A5
A1 (Best)	-	LE	ME	LE	VE
Others-to-worst	A1	A2	A3	A4	A5
A2 (Worst)	LE	-	VE	ME	LE
Level 3 between A1, A2, A3, A4, A5 for C32					
Best-to-others	A1	A2	A3	A4	A5
A1 (Best)	-	ME	LE	ME	LE
Others-to-worst	A1	A2	A3	A4	A5
A4 (Worst)	ME	VE	LE	-	ME
Level 3 between A1, A2, A3, A4, A5 for C33					
Best-to-others	A1	A2	A3	A4	A5
A3 (Best)	LE	ME	-	LE	VE
Others-to-worst	A1	A2	A3	A4	A5
A1 (Worst)	-	VE	LE	ME	ME
Level 3 between A1, A2, A3, A4, A5 for C41					
Best-to-others	A1	A2	A3	A4	A5
A5 (Best)	LE	VE	ME	LE	-
Others-to-worst	A1	A2	A3	A4	A5
A2 (Worst)	ME	-	LE	LE	VE
Level 3 between A1, A2, A3, A4, A5 for C42					
Best-to-others	A1	A2	A3	A4	A5
A3 (Best)	AE	LE	-	VE	ME
Others-to-worst	A1	A2	A3	A4	A5
A5 (Worst)	ME	VE	ME	LE	-
Level 3 between A1, A2, A3, A4, A5 for C43					
Best-to-others	A1	A2	A3	A4	A5
A3 (Best)	VE	LE	-	ME	AE
Others-to-worst	A1	A2	A3	A4	A5
A4 (Worst)	LE	VE	ME	-	LE
Level 3 between A1, A2, A3, A4, A5 for C51					
Best-to-others	A1	A2	A3	A4	A5
A4 (Best)	ME	LE	LE	-	VE
Others-to-worst	A1	A2	A3	A4	A5
A1 (Worst)	-	ME	VE	ME	LE

Table 4. *Cont.*

Level 3 between A1, A2, A3, A4, A5 for C52					
Best-to-others	A1	A2	A3	A4	A5
A2 (Best)	LE	-	VE	ME	AE
Others-to-worst	A1	A2	A3	A4	A5
A1 (Worst)	-	LE	ME	VE	ME
Level 3 between A1, A2, A3, A4, A5 for C53					
Best-to-others	A1	A2	A3	A4	A5
A4 (Best)	VE	ME	VE	-	LE
Others-to-worst	A1	A2	A3	A4	A5
A3 (Worst)	ME	LE	-	AE	ME

4.2.2. Minimisation of the Absolute Gaps Using the Fuzzy BWM

Based on the collected information from the pairwise comparisons, twenty-one optimization problems for all pairwise comparisons can be formulated in order to examine the adjusted weights and priority vectors, according to the proposed methodology presented in Section 3.2. Regarding the optimization process at level 1, the non-linearly constrained optimization problem to evaluate the adjusted weights between C1, C2, C3, C4, and C5 is formulated as in Appendix A. According to the properties of fuzzy set theories and the fuzzy BWM [23], the constraints of the optimization problem can be simplified. Moreover, the membership functions of criteria are defined in triangular shapes, where the membership function values are initialized randomly between [0, 1], complying with Equation (6). In addition, a large number, for example, 999, is set for the value ξ for the commencement of the optimization process. When substituting the membership function values to the optimization problem, it can be solved to obtain the adjusted weights for the five criteria. In this case study, the optimization problem is solved using the GRG Nonlinear in the Excel Solver environment.

By doing so, the optimal weights for the five criteria are [0.5218, 0.1631, 0.0917, 0.0495, 0.1739] for C1, C2, C3, C4, and C5, respectively, using the conversion of GMIR with $\xi^* = 1.73$. To measure the consistency of the results from the use of the fuzzy BWM, the consistency ratio (CR) can be measured, in which a small CR value, and even close to zero, is preferred. The CR value is calculated by dividing the obtained value ξ^* by the consistency index (CI), where the CI is the maximum possible ξ value. The CI value between [0, 1] can be determined through solving a quadradic equation on the highest linguistic term used in the optimization problem, as in Equation (13), where u_0 denotes the upper bound fuzzy number of the linguistic term. Table 5 shows the consistency index for the linguistic terms defined in Tables 1 and 2. Therefore, the CR of using fuzzy BWM for analyzing the pairwise comparison at level 1 is 1.73/13.772 = 0.1256, which is acceptable for the decision makers about the decision-making process of the NPIS.

$$\mathrm{CI}^2 - (1 + 2u_0)\mathrm{CI} + ({u_0}^2 - u_0) = 0 \quad (13)$$

Table 5. Consistency index for the linguistic terms.

Labels of Linguistic Terms	**Fuzzy Number**	**Consistency Index (CI)**
EI/EE	(1, 1, 1)	3
LI/LE	(2, 3, 4)	7.2323
SI/ME	(4, 5, 6)	10
VI/VE	(6, 7, 8)	12.531
AI/AE	(8, 9, 9)	13.772

4.2.3. Weight Aggregation and Idea Ranking

When the procedures stated in Section 4.2.2 are repeated at levels 2 and 3, the adjusted weights for criteria and sub-criteria can be determined, while the priority vectors for the alternatives are formulated. Therefore, it is found that the adjusted weights for sub-criteria at level 2 are presented as shown in Table 6. For the priority vectors, the results of using fuzzy BWM to measure different alternatives are presented in Table 7. By combining the adjusted weights and priority vectors, the composited weights for the alternatives can be determined. For example, the composited weight for the alternative A1 is calculated by the following:

Table 6. Adjusted weights obtained from pairwise comparison at level 2.

	Sub-Criteria at Level 2			
	C11	C12	C13	ξ^*
Weight	0.7190	0.0972	0.1838	*1*
	C21	C22	C23	ξ^*
Weight	0.1758	0.7470	0.0772	*0.8599*
	C31	C32	C33	ξ^*
Weight	0.0750	0.3250	0.6000	*1*
	C41	C42	C43	ξ^*
Weight	0.1935	0.1745	0.6321	1.6277
	C51	C52	C53	ξ^*
Weight	0.0720	0.2983	0.6297	0.8599

Table 7. Summary of the results in the new product idea selection (NPIS) using the fuzzy best-worst method (BWM).

Sub-Criterion	**A1**	**A2**	**A3**	**A4**	**A5**	ξ^*
C11	0.3013	0.4112	0.1841	0.0586	0.0448	4.7251
C12	0.3281	0.1572	0.0410	0.0636	0.4100	5.0000
C13	0.4316	0.2536	0.1190	0.1273	0.0685	3.2984
C21	0.1156	0.2085	0.1244	0.4999	0.0516	4.7251
C22	0.2424	0.4873	0.0612	0.1245	0.0846	3.0000
C23	0.3261	0.1047	0.0694	0.4530	0.0467	4.7251
C31	0.2998	0.0503	0.1860	0.4170	0.0470	3.2984
C32	0.3753	0.1958	0.2798	0.0489	0.1002	3.0000
C33	0.0697	0.2527	0.4459	0.1130	0.1187	3.4714
C41	0.2015	0.0527	0.1094	0.2079	0.4285	1.1551
C42	0.0967	0.2049	0.4910	0.1441	0.0633	3.7251
C43	0.0856	0.2998	0.4782	0.0659	0.0705	2.4689
C51	0.0412	0.2773	0.3267	0.2936	0.0612	2.1564
C52	0.0587	0.4025	0.1006	0.3689	0.0693	4.0000
C53	0.1066	0.1741	0.0476	0.4606	0.2112	2.7251
Composited weight	0.2458	0.3284	0.1634	0.1617	0.1007	

$0.5218\cdot(0.7190\cdot0.3013 + 0.0972\cdot0.3281 + 0.1838\cdot0.4316) + 0.1631\cdot(0.1758\cdot0.1156 + 0.7470\cdot0.2424 + 0.0772\cdot0.3261) + 0.0917\cdot(0.0750\cdot0.2998 + 0.3250\cdot0.3753 + 0.6\cdot0.0697) + 0.0495\cdot(0.1935\cdot0.2015 + 0.1745\cdot0.0967 + 0.6321\cdot0.0856) + 0.1739\cdot(0.0720\cdot0.0587 + 0.2983\cdot0.0587 + 0.6297\cdot0.1066) = 0.2458.$

By repeating the same approaches, all the composited weights for all the alternatives can be computed. It is shown that the composited weights for A1, A2, A3, A4, and A5 are [0.2239, 0.2862, 0.1907, 0.1841, 0.1151], respectively. By ranking the above results, the most appropriate new product idea is A2, which has the highest composited weight value.

5. Results and Discussion

The feasibility of the proposed methodology was verified through the case study in Section 4, where the process for conducting NPIS at the fuzzy front end of innovation is demonstrated. Through analysing five major criteria and fifteen sub-criteria, the most appropriate new product idea, namely A2, is selected with the highest composited weight of 0.3284 at the specific decision maker illustrated in the case study. By repeating the whole approach for the second decision maker, the average composited weights for five alternatives are [0.2192, 0.3568, 0.1617, 0.1409, 0.1110], thus the ranking of the new product ideas is expressed as {A2, A1, A3, A4, A5}. To further evaluate the proposed methodology, the sub-sections of (i) evaluation of the consistency index, (ii) comparison with existing MCDM methods, and (iii) contributions and managerial implications are discussed.

5.1. Evaluation of the Consistency Index

Apart from measuring the consistency index at level 1, the same evaluation is extended to levels 2 and 3 in order to ensure the entire measurement of the fuzzy BWM is acceptable by the decision makers. According to Table 6, the ξ^* values can be aggregated with the consistency index, which are calculated using Equation (13) to determine the corresponding consistency ratios. Its results are illustrated as shown in Figure 4, where a reference line (consistency ratio is 1) is added as the ceiling point. It is found that the consistency indexes of all five pairwise comparisons are less than 0.2, with an average of 0.09, which shows that the pairwise comparisons are satisfactory and acceptable. Similarly, the consistency indexes of the pairwise comparisons at the level 3 are presented in Figure 5, where the average consistency index is 0.2209. The performance of the measurement consistency is acceptable by the case company, which lies on its acceptable threshold. Therefore, the results obtained by using the proposed methodology are trustworthy for the case company to select the most appropriate new product ideas for entering the formal product development process.

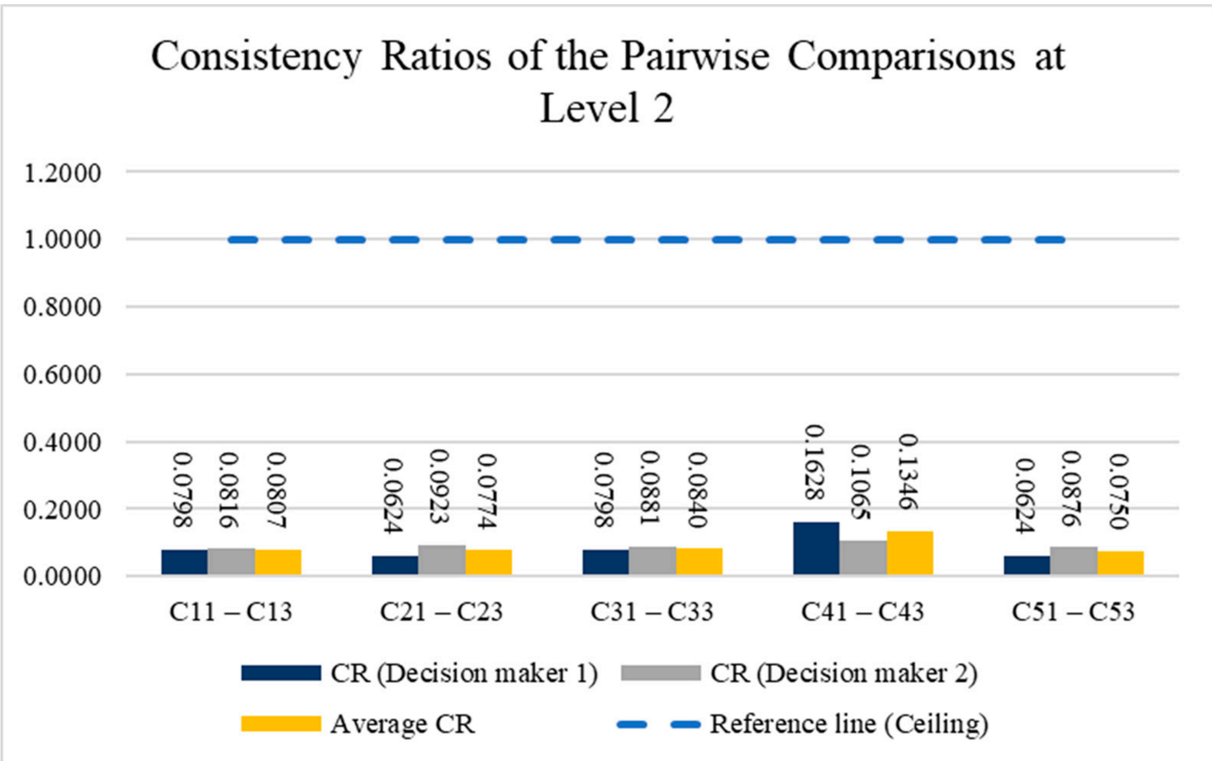

Figure 4. Plot of consistency ratios (CRs) of the pairwise comparisons at level 2.

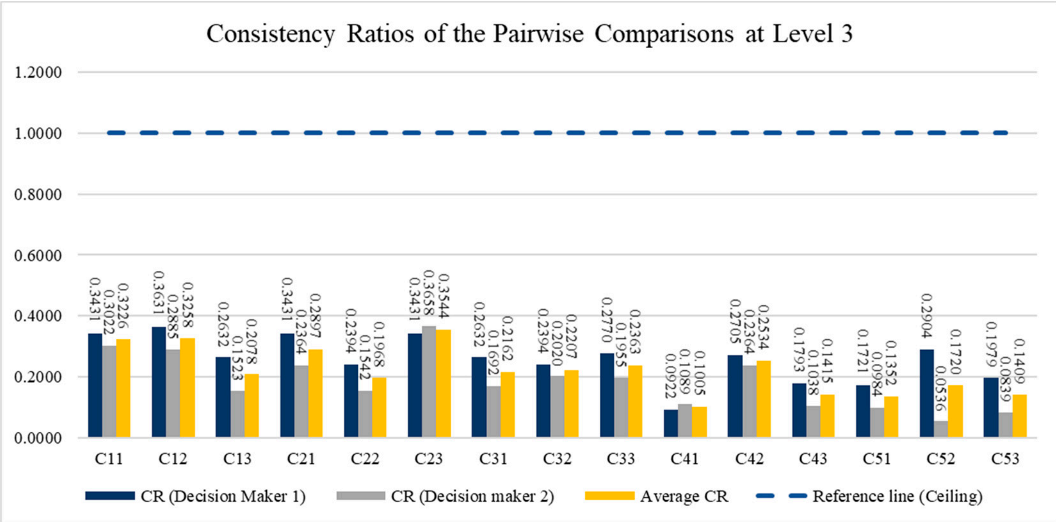

Figure 5. Plot of consistency ratios of the pairwise comparisons at level 3.

5.2. Comparisons with Using Fuzzy AHP

Regarding the proposed methodology, the fuzzy BWM, one of the MCDM methods, is selected as the core analytics method to establish and evaluate the pairwise comparison. To highlight the value of the proposed methodology, a qualitative comparison between the fuzzy BWM and fuzzy AHP is conducted, in which fuzzy AHP is widely exploited in numerous multi-criteria decision-making problem. First and foremost, the proposed methodology using the fuzzy BWM requires a smaller number of pairwise comparisons, i.e., $2n - 3$ comparisons, compared with $n(n-1)/2$ comparisons in the fuzzy AHP, where n refers to the number of criteria. Moreover, the above statement is true when n is greater or equal to 3. In other words, the effort on completing the pairwise comparisons in the fuzzy BWM can be lesser when the number of criteria is larger than or equal to 3. With having a smaller number of pairwise comparisons, a high degree of measurement consistency can be achieved in a relatively effective and simple manner. Moreover, the use of fractional numbers to construct the comparison matrix can be avoided, which is more user-friendly to derive weights between various selection criteria. On the other hand, the fuzzy AHP has advantages on computation, which only involve some basic mathematical calculation. It is convenient and user-friendly to realise the operations of the fuzzy AHP. However, the deployment of the fuzzy BWM requires solving the non-linear optimisation problem to minimise the absolute gap subject to several constraints. Subsequently, an optimisation engine, such as Excel Solver, is necessary to derive the weights between various selection criteria. When the number of criteria increases, it is expected that more resources on the optimisation engine are needed to solve the optimisation problem. Although some barriers on using the fuzzy BWM are observed, the advantages on conducting a smaller number of pairwise comparisons outweigh the drawbacks. In addition, to compare them qualitatively, the evaluations of weighted spearman's rank correlation coefficient (r_ω) and rank similarity coefficient (WS) are conducted to examine the ranking performance between the fuzzy BWM and fuzzy AHP [31], as in Equations (14) and (15). R_{xi} and R_{yi} represent the expected and estimated ranking results at alternative i, respectively, while N denotes the total number of alternatives. Generally speaking, large values of r_ω and WS are preferred, while the WS, which is higher than 0.808, refers to high similarity between the expected and estimated ranking. Consequently, the validation results are presented in Table 8 with ranking five alternatives, as discussed in the case study. It is found that the use of the fuzzy BWM for the NPIS obtained highly similar ranking results compared with the expected ranking, whereas the performance of fuzzy AHP is relatively poor. Moreover, the WS of using fuzzy BWM is 0.8542, which is higher than 0.808, so the results obtained from the fuzzy BWM indicate a high similarity to the expected ranking. Therefore, deploying the fuzzy BWM in the NPIS and other selection problems is preferable to using fuzzy AHP.

$$r_\omega = 1 - \frac{6 \cdot \sum_{i=1}^{N} \{(R_{xi} - R_{yi})^2 \cdot [(N - R_{xi} + 1) + (N - R_{yi} + 1)]\}}{N^4 + N^3 - N^2 - N} \tag{14}$$

$$WS = 1 - \sum_{i=1}^{N} [2^{-R_{xi}} \cdot \frac{|R_{xi} - R_{yi}|}{\max(|R_{xi} - 1|,\ |R_{xi} - N|)}] \tag{15}$$

Table 8. Comparison of r_ω and rank similarity coefficient (WS) in the case study. AHP, analytical hierarchy process.

Alternatives	Expected Ranking	Fuzzy AHP	Fuzzy BWM
A1	3	2	2
A2	1	3	1
A3	2	1	3
A4	4	4	4
A5	5	5	5
r_ω	1	0.6000	0.8833
WS	1	0.6042	0.8542

6. Conclusions

This study exploited the fuzzy BWM to establish a comprehensive methodology for addressing the challenges in the domain of NPIS at the FFE of innovation. At the FFE stage, plenty of unstructured information should be considered for proposing new product ideas, which makes it difficult to judge the appropriateness of new product ideas in the market. Moreover, the NPD is critical for the survival and competitive edge of a business organisation. Thus, a systematic approach to perform NPIS is desired to distil the most profitable, sustainable, and competitive new product idea. In this study, the hierarchical structure is established to overcome the selection problem about the NPIS, while the fuzzy BWM is deployed to select the most appropriate new product idea based on decision makers' rating between various criteria. A detail implementation of the proposed methodology is presented to demonstrate the process from pairwise comparisons to the determination of alternatives' weights. Consequently, the new product ideas can be ranked according to the weights systematically in terms of finance, marketing, engineering, manufacturing, and sustainability. The contribution of this study has two facets. First, an efficient methodology for the NPIS is proposed using the fuzzy BWM rather than using typical MCDM methods, such as fuzzy AHP. Second, the consideration of sustainability is included in the hierarchical structure for the NPIS, which aligns to the initiative of circular economy in the world. This implies that new products developed in the market should not only consider the profitability and engineering requirements, but also environmentally-friendly and green protection measures. Ultimately, the NPD can be more sustainable in the market, which can have a positive influence on the company reputation. For future research, additional case scenarios about the NPIS can be considered to validate the performance of the proposed methodology, where the value of MCDM methods in the NPD process can be highlighted. Moreover, benchmarking with other existing MCDM methods can be considered to select the most appropriate method in the designated domain, and thus a selection mechanism for the MCDM methods with a bunch of criteria and sub-criteria, such as the complexity of pairwise comparisons, can be established.

Author Contributions: Conceptualization, S.M.L. and Y.P.T.; methodology, S.M.L.; software, Y.P.T. and H.Y.L.; validation, Y.P.T. and H.Y.L.; formal analysis, S.M.L., Y.P.T. and H.Y.L.; data curation, S.M.L.; writing—original draft preparation, S.M.L.; writing—review and editing, Y.P.T.; supervision, F.T.S.C.; project administration, F.T.S.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data available on request due to the restriction of business confidentiality.

Acknowledgments: The authors would like to thank the Engineering Doctorate Programme, Faculty of Engineering of The Hong Kong Polytechnic University, and Pacific Business Machine Limited for inspiring the development of this research study. Sincere gratitude is extended to Jack C.H. WU at The Hang Seng University of Hong Kong for supporting the research.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

In this appendix, the weight evaluation between C1, C2, C3, C4, and C5 is illustrated with the adoption of the fuzzy BWM and group decision-making process, where the fuzzy weights of C1, C2, C3, C4, and C5 are expressed as (l_1, m_1, u_1), (l_2, m_2, u_2), (l_3, m_3, u_3), (l_4, m_4, u_4), and (l_5, m_5, u_5), respectively. According to Table 3, C1 is selected as the best criterion, while C4 is chosen as the worst criterion. Equation (A1) shows the complete form of the optimization problem including the objective function and constraints according to Section 3.2. By making use of fuzzy number operators and GMIR, the optimization problem stated in Equation (A1) can be simplified to Equation (A2).

$$\min.\ \xi \text{s.t.} \begin{cases} \left|\frac{w_1}{w_2} - (4,5,6)\right| \leq \xi \\ \left|\frac{w_1}{w_3} - (6,7,8)\right| \leq \xi \\ \left|\frac{w_1}{w_4} - (8,9,9)\right| \leq \xi \\ \left|\frac{w_1}{w_5} - (2,3,4)\right| \leq \xi \\ \left|\frac{w_2}{w_4} - (4,5,6)\right| \leq \xi \\ \left|\frac{w_3}{w_4} - (2,3,4)\right| \leq \xi \\ \left|\frac{w_5}{w_4} - (4,5,6)\right| \leq \xi \\ \frac{1}{6} \times \sum_{i=1}^{5} (l_i + 4m_i + u_i) = 1 \\ 0 \leq l_1 \leq m_1 \leq u_1 \\ 0 \leq l_2 \leq m_2 \leq u_2 \\ 0 \leq l_3 \leq m_3 \leq u_3 \\ 0 \leq l_4 \leq m_4 \leq u_4 \\ 0 \leq l_5 \leq m_5 \leq u_5 \\ \xi \geq 0 \end{cases} \tag{A1}$$

$$\min.\ \xi = (k,\ k,\ k) \text{ s.t. } \begin{cases} \left|\frac{l_1}{u_2} - 4\right| \leq k; \left|\frac{m_1}{m_2} - 5\right| \leq k; \left|\frac{u_1}{l_2} - 6\right| \leq k \\ \left|\frac{l_1}{u_3} - 6\right| \leq k; \left|\frac{m_1}{m_3} - 7\right| \leq k; \left|\frac{u_1}{l_3} - 8\right| \leq k \\ \left|\frac{l_1}{u_4} - 8\right| \leq k; \left|\frac{m_1}{m_4} - 9\right| \leq k; \left|\frac{u_1}{l_4} - 9\right| \leq k \\ \left|\frac{l_1}{u_5} - 2\right| \leq k; \left|\frac{m_1}{m_5} - 3\right| \leq k; \left|\frac{u_1}{l_5} - 4\right| \leq k \\ \left|\frac{l_2}{u_4} - 4\right| \leq k; \left|\frac{m_2}{m_4} - 5\right| \leq k; \left|\frac{u_7}{l_4} - 6\right| \leq k \\ \left|\frac{l_3}{u_4} - 2\right| \leq k; \left|\frac{m_3}{m_4} - 3\right| \leq k; \left|\frac{u_3}{l_4} - 4\right| \leq k \\ \left|\frac{l_5}{u_4} - 4\right| \leq k; \left|\frac{m_5}{m_4} - 5\right| \leq k; \left|\frac{u_5}{l_4} - 6\right| \leq k \\ \frac{1}{6} \times \sum_{i=1}^{5} (l_i + 4m_i + u_i) = 1 \\ 0 \leq l_1 \leq m_1 \leq u_1 \\ 0 \leq l_2 \leq m_2 \leq u_2 \\ 0 \leq l_3 \leq m_3 \leq u_3 \\ 0 \leq l_4 \leq m_4 \leq u_4 \\ 0 \leq l_5 \leq m_5 \leq u_5 \\ k \geq 0 \end{cases} \tag{A2}$$

References

1. Chen, Y.J.; Chien, C.F. An empirical study of demand forecasting of non-volatile memory for smart production of semiconductor manufacturing. *Int. J. Prod. Res.* **2018**, *56*, 4629–4643. [CrossRef]
2. Mor, R.S.; Jaiswal, S.K.; Singh, S.; Bhardwaj, A. Demand Forecasting of the Short-Lifecycle Dairy Products. In *Understanding the Role of Business Analytics*; Springer: Singapore, 2019; pp. 87–117.
3. The Product Launch: 31 Statistics to Keep in Mind. Available online: https://learn.g2.com/product-launch-statistics (accessed on 2 July 2020).
4. Marquis, J.; Deeb, R.S. Roadmap to a Successful Product Development. *IEEE Eng. Manag. Rev.* **2018**, *46*, 51–58. [CrossRef]
5. Cooper, R.G. The drivers of success in new-product development. *Ind. Mark. Manag.* **2019**, *76*, 36–47. [CrossRef]
6. Salgado, E.G.; Salomon, V.A.; Mello, C.H. Analytic hierarchy prioritisation of new product development activities for electronics manufacturing. *Int. J. Prod. Res.* **2012**, *50*, 4860–4866. [CrossRef]
7. Xin, J.Y.; Yeung, A.C.; Cheng, T.C.E. Radical innovations in new product development and their financial performance implications: An event study of US manufacturing firms. *Oper. Manag. Res.* **2008**, *1*, 119–128. [CrossRef]
8. Pitta, D.; Pitta, E. Transforming the nature and scope of new product development. *J. Prod. Brand. Manag.* **2012**, *21*, 35–46. [CrossRef]
9. Pun, K.F.; Yiu, M.Y.R.; Chin, K.S. Developing a self-assessment model for measuring new product development performance: An AHP approach. *Int. J. Adv. Oper. Manag.* **2010**, *2*, 57–79. [CrossRef]
10. Wu, Y.; Zhou, F.; Kong, J. Innovative design approach for product design based on TRIZ, AD, fuzzy and Grey relational analysis. *Comput. Ind. Eng.* **2020**, *140*, 106276. [CrossRef]
11. Mandolfo, M.; Chen, S.; Noci, G. Co-creation in new product development: Which drivers of consumer participation? *Int. J. Eng. Bus. Manag.* **2020**, *12*. [CrossRef]
12. Hama Kareem, J.A. The impact of intelligent manufacturing elements on product design towards reducing production waste. *Int. J. Eng. Bus. Manag.* **2019**, *11*. [CrossRef]
13. Zhang, Z.; Guan, Z.; Xie, X. Innovation development and capability evolution for traditional machinery manufacturing enterprises based on genetic algorithm. *Enterp. Inf. Syst.* **2020**, 1–23. [CrossRef]
14. Liu, Z.; Pu, J. Analysis and research on intelligent manufacturing medical product design and intelligent hospital system dynamics based on machine learning under big data. *Enterp. Inf. Syst.* **2019**, 1–15. [CrossRef]
15. Sääksjärvi, M.; Hellén, K. Idea selection using innovators and early adopters. *Eur. J. Innov. Manag.* **2019**, *22*, 585–599. [CrossRef]
16. Banken, V.; Ilmer, Q.; Seeber, I.; Haeussler, S. A method for Smart Idea Allocation in crowd-based idea selection. *Decis. Support Syst.* **2019**, *124*, 113072. [CrossRef]
17. What Do We Know about New Product Idea Selection. Available online: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.130.7712&rep=rep1&type=pdf (accessed on 15 December 2020).
18. Santos, K.; Loures, E.; Piechnicki, F.; Canciglieri, O. Opportunities assessment of product development process in Industry 4.0. *Procedia Manuf.* **2017**, *11*, 1358–1365. [CrossRef]
19. Silva, E.M.; Jardim-Goncalves, R. Cyber-Physical Systems: A multi-criteria assessment for Internet-of-Things (IoT) systems. *Enterp. Inf. Syst.* **2019**, 1–20. [CrossRef]
20. Lam, H.Y.; Tsang, Y.P.; Wu, C.H.; Tang, V. Data analytics and the P2P cloud: An integrated model for strategy formulation based on customer behaviour. *Peer Peer Netw. Appl.* **2020**, 1–18. [CrossRef]
21. Czekster, R.M.; Webber, T.; Jandrey, A.H.; Marcon, C.A.M. Selection of enterprise resource planning software using analytic hierarchy process. *Enterp. Inf. Syst.* **2019**, *13*, 895–915. [CrossRef]
22. Rezaei, J. Best-worst multi-criterion decision-making method. *Omega* **2015**, *53*, 49–57. [CrossRef]
23. Guo, S.; Zhao, H. Fuzzy best-worst multi-criterion decision-making method and its applications. *Knowl. Based Syst.* **2017**, *121*, 23–31. [CrossRef]
24. Shekhovtsov, A.; Kozlov, V.; Nosov, V.; Sałabun, W. Efficiency of Methods for Determining the Relevance of Criteria in Sustainable Transport Problems: A Comparative Case Study. *Sustainability* **2020**, *12*, 7915. [CrossRef]
25. Relich, M.; Pawlewski, P. A fuzzy weighted average approach for selecting portfolio of new product development projects. *Neurocomputing* **2017**, *231*, 19–27. [CrossRef]
26. Yao, X.; Askin, R. Review of supply chain configuration and design decision-making for new product. *Int. J. Prod. Res.* **2019**, *57*, 2226–2246. [CrossRef]
27. Rodrigues, V.P.; Pigosso, D.C.; McAloone, T.C. Process-related key performance indicators for measuring sustainability performance of ecodesign implementation into product development. *J. Clean. Prod.* **2016**, *139*, 416–428. [CrossRef]
28. Gani, A.N.; Assarudeen, S.M. A new operation on triangular fuzzy number for solving fuzzy linear programming problem. *Appl. Math. Sci.* **2012**, *6*, 525–532.
29. Chen, S.H.; Wang, S.T.; Chang, S.M. Some properties of graded mean integration representation of LR type fuzzy numbers. *Tamsui Oxford J. Inf. Math. Sci.* **2006**, *22*, 185.
30. Bozanic, D.; Tešić, D.; Milićević, J. A hybrid fuzzy AHP-MABAC model: Application in the Serbian Army–The selection of the location for deep wading as a technique of crossing the river by tanks. *Decis. Mak. Appl. Manag. Eng.* **2018**, *1*, 143–164. [CrossRef]
31. Sałabun, W.; Urbaniak, K. A new coefficient of rankings similarity in decision-making problems. In *International Conference on Computational Science*; Springer: Cham, Switzerland, 2020; pp. 632–645.